BASELINE REMOVAL FROM EMG RECORDINGS

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***Abstract*- A method for baseline (BL) removal in needle EMG records is presented. Different processing techniques are sequentially used. Firstly motor unit action potentials (MUAPs) are extracted from the signal by means of a wavelet transform-based procedure. Potential-free, discontinuous segments are thus obtained, whose fluctuation is assumed to be related to BL wander. These signals are then time averaged to attenuate the effect of noise and of low amplitude MUAPs originated distant from the electrode. Spline interpolation is then used to build a continuous reconstructed signal whose spectral characteristics approximate that of the real BL. The spectrum of this signal is estimated by AR modeling and an FIR filter is implemented accordingly for filtering out the BL low frequency components from the original EMG signal. Two merit figures are devised, which measure the degree of BL fluctuation present in an EMG record. These figures are used to compare our method with the conventional approach which consider the BL to be a constant value. Experiments for BL removal from real and simulated EMG signals are carried out. The superior performance of our approach is shown regarding these merit figures and visual inspection.**

***Keywords* – EMG, baseline removal, MUAP**

I. INTRODUCTION

Motor unit action potential (MUAP) expresses the electrical activity of the muscle fibers of a motor unit (MU) recorded from a needle electrode. The shape of MUAP waveforms, and their similarity in consecutive appearances contain valuable information about the state of a muscle, helping to distinguish between myopathic, neurogenic or normal states and to measure the degree of abnormality. MUAP analysis is thus a daily-work procedure in clinical electromyography (EMG). For MUAP characterization different parameters are used: duration, amplitude, area, number of turns and phases, jiggle, etc. [1], [2]. The measurement of these parameters is influenced by baseline (BL) fluctuation along the recorded signal. Particularly relevant is this influence on duration, and jiggle (as measured by the CAD parameter [2], [3]), as these include in their definition amplitude criteria with respect to the BL. Therefore a precise estimation of the BL will help making measurements of these parameters more accurate.

Current methods consider the BL to be constant throughout the MUAP: they either average the samples in the segments at both ends of the MUAP discharge (typically 3 ms segments are taken in 25 ms registers in which the main spike of the MUAP occupies the central position) [1]; or else just give the BL a zero level (system ground).

We regard the BL as a low frequency fluctuation present in the recorded signal (Fig. 1) due to artifacts of different nature: the movement of the recording needle relative to the muscle, variation of skin potential induced by the needle, electrical drifts in the acquisition equipment, etc. But above all, the main source of BL fluctuation is the activity of distant MUs, which produce potentials that cannot even be identified as MUAPs, as they only provoke a mild BL wander. In the EMG signal, there also appear "secondary" potentials, not to be confused with the previous. They originate relatively far from the electrode and are low-amplitude and smooth, and thus not valid for EMG clinical analysis, but still considered as real MUAPs and not as BL components.

Several methods for BL removal have been applied to other biomedical signals, such as ECG [4], [5]. They heavily rely upon "a-priori" knowledge of the BL frequency band. In EMG, BL frequency components are not too well known and are subject to high variability across different muscles, individuals and recordings. In the method we present in this paper several signal processing techniques are used to estimate the spectrum of the BL present in an EMG recording. A convenient filter is then used to filter out the BL frequency components.

II. MATERIAL

Twenty EMG real signals from the right tibialis anterior muscle of a 39 year-old healthy man were analyzed. The EMG signals were recorded at different degrees of voluntary contraction using an electromyograph (Counterpoint, Dantec Co., Denmark) and disposable concentric needle electrodes. After antialiasing filtering, signals were sampled at 2.4 kHz (a higher sampling frequency was not required in this study).

Ten simulated signals were also analyzed. Real MUAP waveforms and secondary potentials were taken as templates to form MUAP trains. Templates were repeated at a determined frequency (between 3 and 12 Hz) for each

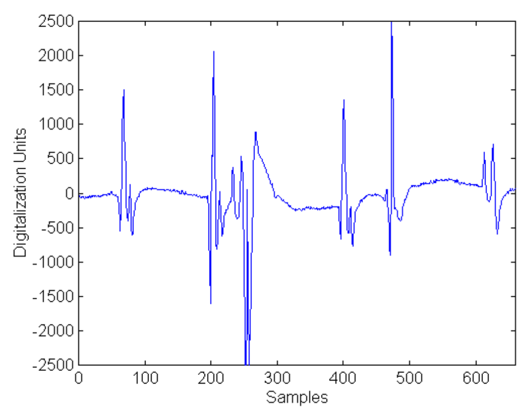

Figure 1. EMG recording: several MUAPs appear on top of a time-varying baseline contamination.

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different train) which was not constant but subject to a small random variation (±2 Hz). Simulated signals were composed of several MUAP trains (between 1 and 5) and corrupted by a secondary potential, white gaussian noise (SNR between 30 and 43 dB) and BL fluctuations (SNR between 14.6 and 28.7 dB). The BL was simulated by filtering zero-mean white gaussian signals with a low-pass Butterwoth filter [6] (cut-off frequencies between 5 and 20 Hz). The characteristic of both signal sets exhibited wide variation with respect to the degree of activity (number of present MUAPs), MUAP duration and spectral range of BL fluctuation.

III. METHODS

The method comprises several sequential phases:

a) estimation of EMG activity level;
b) segmentation of the EMG signal into segments containing MUAPs and free-MUAP segments (BL);
c) BL spectral characterization;
d) BL filtering.

In each phase, different alternatives were tested and those which yielded better results were selected. In the sequel we describe these phases.

A. Estimation of the level of EMG activity

The number of MUAPs present in an EMG recording (i.e., level of EMG activity) depends on the contraction level of the muscle. With a low contraction level, few MUs are activated and the record presents relatively long and steady BL segments, with scattered MUAPs. As the contraction force increases, more MUs are recruited and the level of EMG activity increases while the BL segments without MUAPs become fewer and shorter. We use the number of spikes per ms as a quantitative measure of the level of EMG activity.

B. MUAP detection

This phase focuses on the MUAP detection and isolation from BL segments, making use of the discrete wavelet transform (DWT). Specifically the non-orthogonal quadratic spline wavelet is used, which has been successfully utilized for the detection of characteristic points in ECG signals [7]. The detection algorithm is similar to that presented in [7] and its applicability is also sustained by the fact that the uniphasic (only-one-peak) shape of this wavelet resembles that of the uniphasic basic components conforming the EMG waveform. Similarly to the QRS detection in EEG, MUAP maxima, minima and zero-crossing points are detected in the EMG signal, and from these, MUAP initial and end points. This part of the process is further split in two subphases: determination of the active segments (AS), (i.e., those signal portions mainly occupied by MUAPs), and fine estimation of the span of these segments.

B.1. Determination of AS. Several steps are carried out:

- DWT computation of the EMG signal and selection of the scale containing most energy (Fig. 2.a);
- First splitting of the signal in active and BL segments: as BL samples normally dwell in a narrower amplitude range than MUAP samples, a histogram with the EMG samples (in the wavelet domain) is built and those samples whose amplitudes appear in the least frequently bin are assigned to AS, while the rest are assigned to BL segments (see thresholds in Fig. 2.a). Histograms of 20 to 100 bins were tested, finding 40-bin histograms as the most convenient.
- Determination of maxima and minima: maxima and minima in AS are detected and considered belonging to different MUAPs or superposition of MUAPs when a maximum is followed by a minimum or vice versa and when these are at least Δt ms apart. We experimentally set up a suitable relation between this delay and the EMG activity: (low activity: Δt=9ms, low-mid activity: Δt=11ms, mid-high activity: Δt=13ms, high activity: Δt=17ms).
- AS extraction: initial and final AS points are estimated by:

$$begining_{segment} = first_i - \frac{1}{3}\left(first_i - end_{i-1}\right) \qquad (1)$$

$$end_{segment} = end_i + \frac{1}{3}\left(first_{i+1} - end_i\right) \qquad (2)$$

where $first_i$ and end_i refer respectively to the first maximum or minimum and the last maximum or minimum pertaining to a certain MUAP or MUAP superposition, and i indexes the different MUAP or MUAP superposition.

B.2. Fine estimation of the initial and final points of the identified AS (Fig. 2.b). Several steps are carried out, some of them equivalent to those in Subphase B.1:

- DWT computation of the EMG signal and selection of the scale containing most energy.
- Second splitting of the signal in active and BL segments: a new histogram-based splitting process, similar to the one previously described is carried out, obtaining more restrictive AS. Here a 40-bin histogram was also chosen.
- Isolated peak elimination: due to the MUAP morphology, the maxima and minima of the DWT signal should appear alternately. Peaks altering this disposition are removed.
- Look for relevant unconsidered peaks: some low amplitude MUAPs may have skipped from the previous processes. They are search for at either side of the AS, using wavelet domain amplitude thresholds, peak-to-peak separation time and sign alternation restrictions.
- Determination of the potential beginning: the onset of the first maximum or minimum in the wavelet transform provides the beginning of the MUAP or MUAP superposition [7]. The DWT causes an artificial delay of 2^{j-1}-2 samples which has to be discounted.
- Determination of the potential end: the end point of the last peak is taken as the end of the potential.

C. BL analysis and spectral characterization

BL spectral characterizing is carried out in this phase, by means of the following steps:

- Averaging of free BL segments: The detected free-BL segments may still contain secondary potentials (low-amplitude, smooth potentials coming from distant MUs) as well as high-frequency noise from diverse origins. To reduce the influence of these artifacts in BL estimation, consecutive samples of these segments are averaged (Fig. 2.c). After testing several intervals lengths (between 3 and 20 ms), intervals of 10 ms were chosen as the most convenient.

- Interpolation: the previously averaged points are interpolated by means of cubic splines, resulting a curve with the appearance of a true BL fluctuation (Fig. 2.c).
- BL spectral characterization: AR spectral estimation [6] is applied to the interpolated signal giving a smooth and high resolution power spectral density (psd) (Fig. 3). As expected, the resulting psd corresponds to a low frequency signal (BL estimate). Its 3-dB bandwidth is then obtained.

D. Filtering (Fig. 2.d)

For the final BL removal, the EMG signal passes a high-pass filter with a cut-off frequency equal to the previous 3-dB bandwidth. A linear phase FIR filter is used so to preserve phase relations among different signal components. We used Remez interchange algorithm for the design of this filter [6].

IV. Results

A. Merit figures

Quantitative evaluation is needed to compare BL removal methods. Two merit figures (F and N) are devised for measuring the degree of BL fluctuation in repeated discharges of the same MU. They are calculated as follows:

1) All the waveforms in the EMG record corresponding to non-overlapped MUAPs are manually selected.
2) These discharges are given time origins so that correlation among them is maximum.
3) Let $Y_k=\{ y_k(1), y_k(2), \ldots, y_k(n)\}$ be the discharge k of the set of n discharges, where $y_k(t)$, is the t sample of Y_k . The two proposed merit figures are defined as:

$$F = \underset{k}{sd}\left(\underset{t}{mean}\left(Y_1\right), .., \ mean\left(Y_m\right) \right) \quad (3)$$

(first the temporal mean of every discharge is calculated; then the standard deviation of all these means is computed).

$$N = \underset{t}{mean}\left(\underset{k}{sd}\left(y_1(t), ..., \ y_m(t)\right) \right) \quad (4)$$

(standard deviation across different discharges is calculated for every sample time; the resulting set of values are then averaged).

BL removal methods can be compared using these figures: lower F and N values are attained when lower BL fluctuation remains, indicating thus better performance.

To first test the validity of F and N, they were used to measure two different sets of simulated signals. The first set was made out of 3 different MUAP trains to which noise (33 dB SNR level) and an artificial BL of varying amplitude (from A to A/6) and low frequency range (5Hz) were added. Table I shows the obtained F and N. Their increasing values with BL growing amplitude, credited these figures as good indicators of the degree of BL fluctuation. In the second set, the same MUAP trains were contaminated by additive noise (33 dB SNR level) and an artificial BL of different frequency ranges (5, 7, 10, 15 and 19 Hz). Although F and N also increased with BL frequency content (Table I), this tendency was not so notorious, not contradicting the previous claim.

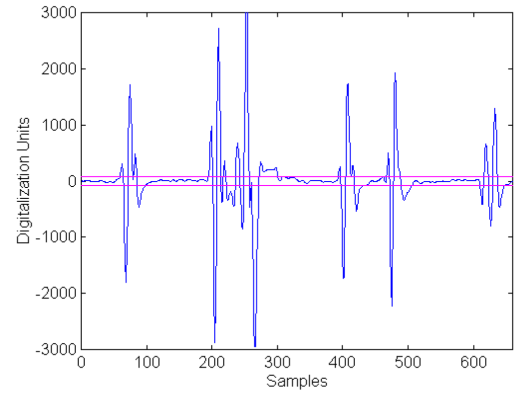

Figure 2.a. DWT and amplitude histogram-based thresholds.

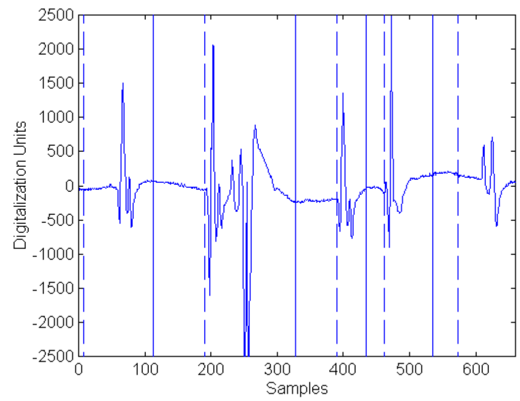

Figure 2.b. Active segments (separated by dashed and continuous lines).

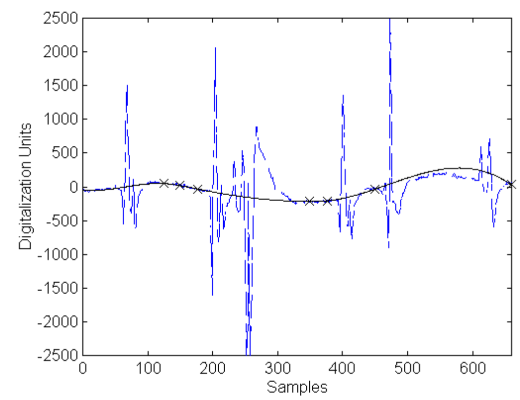

Figure 2.c. Free-BL averages (x) and interpolated curve.

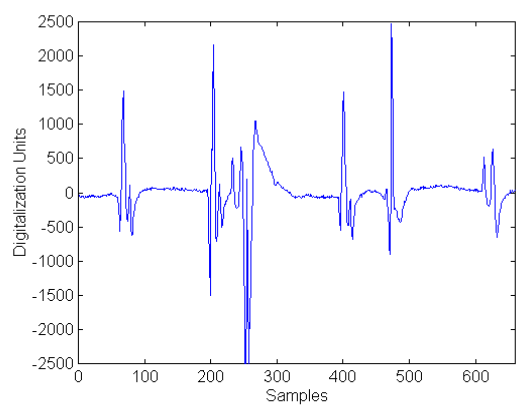

Figure 2.d. Final BL-corrected signal.

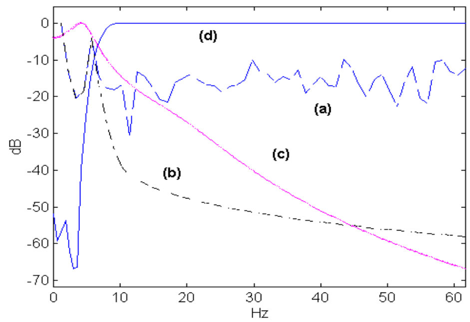

Figure 3. EMG signal spectrum (a), estimated BL (difference between initial signal and final filtered signal) spectrum (b), AR model spectrum (c), and high-pass filter frequency response (d).

B. Results from simulation and real signals

Table II shows the mean and standard deviation of *F* and *N* values obtained by the conventional method [1] and ours, when applied to the sets of real and simulated signals. The significant lower values manifest the superior performance of our method.

C. Visual assessment.

Visual inspection of the analyzed signals proved satisfactory results (compare Fig. 1 and Fig. 2.d), except in the extreme cases of high activity level or the presence of potentials with unusually long tails.

IV. Discussion

It can be noticed that the differences between successive occurrences of the same bioelectric phenomenon (i.e., MUAP discharges) are lower when our method is applied than when simply removing a constant BL level. From this we infer that BL cause an artifactual fluctuation that our method is able to counterbalance in some extent.

TABLE I

F and *N* values of the three motor units (MU 1, 2 and 3) composing the simulated EMG records with varying degrees of BL amplitude and frequency content.

		MU 1		MU 2		MU 3	
		F	***N***	***F***	***N***	***F***	***N***
BL amp.	**A/6**	40,5	41,8	11,9	15,0	26,9	28,6
	A/5	48,1	49,2	14,2	17,1	32,3	33,7
	A/4	59,4	60,4	17,8	20,6	40,4	41,6
	A/3	78,4	79,12	23,7	26,6	53,9	55,0
	A/2	116,3	117,0	35,5	38,8	80,9	81,9
	A	230,0	230,7	70,9	76,3	161,8	163,2
BL freq.	**5**	59,5	60,4	17,8	20,6	40,4	41,6
	7	51,0	52,3	36,1	37,2	76,5	77,1
	10	53,3	55,7	77,6	79,8	83,1	84,3
	15	74,9	79,1	54,9	71,3	99,2	101,7

TABLE II

F and *N* mean and standard deviation values obtained by the conventional method (Orig.) and ours (New).

		F		N	
		Mean (std)	***T-test***	***Mean (std)***	***T-test***
Real signals	Orig.	143,7 (260,1)	p < 0,01	387,5 (325,8)	p < 0,01
	New	129,9 (254,8)		381,9 (328,1)	
Simul. Signals	Orig.	59,8 (33,4)	p < 0,001	77,5 (54,8)	p < 0,010
	New	37,0 (23,4)		53,76 (54,7)	

When the EMG signal contains waveforms with small-slope and long tails, determination of their ends points may turn hazardous. In such cases averaging cannot fully cope with these terminal waveform portions, and spectral characterization becomes inaccurate.

In the case of high EMG activity the method efficacy is also reduced: as this activity grows, free-BL segments are sparser and shorter, splines curvature is abnormally high in the interpolated curve, and the BL course is not followed too precisely, yielding a final distorted estimation of the BL spectrum. However, this limitation is not too problematic as EMG signals with such activity levels are unacceptable for clinical practice.

The proposed BL removal method can be used for obtaining more precise measurements of the conventional MUAP parameters [1], [2], although the potential benefit of this enhancement has still to be explored. Moreover, being a method designed to be applied on free-run EMG signals, it may eventually be implemented as part of EMG decompositions systems for automatic MUAP extraction.

V. Conclusions

The proposed method for BL removal, based in frequency characterization of MUAP-free EMG segments has proven superior to conventional procedures, that consider the BL to be constant along the MUAP record or the whole EMG signal. Its main limitation is the presence of MUAPs with a long tail that cannot be completely put aside from the BL segments, altering thus the BL frequency estimation.

Its potential use for enhancing MUAP parameter measurements and real-time acquisitions appears promising.

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